Large scale simulations with parallel annealing algorithm

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Large scale simulations with parallel annealing algorithm

in collaboration with

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RSCF 14-21-11058 and DIONICOS



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3BM and Supercomputers

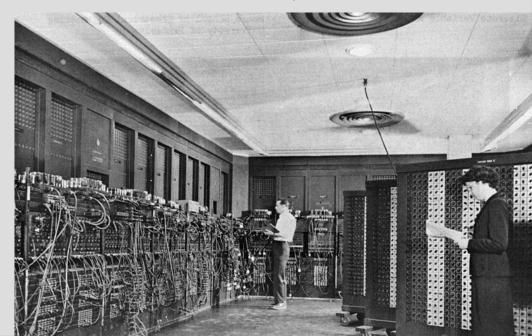
XX century - fall of 40th – beginning of 50th:

- nuclear project (hudrodynamics)
- Monte Carlo method von Neumann, Ulam, Metropolis-Rosenblut²-Teller²
- Fermi-Pasta-Ulam problem
- Random Number Problem von Neumann, Lehmer

M9CM, 1950



ENIAC, 1944

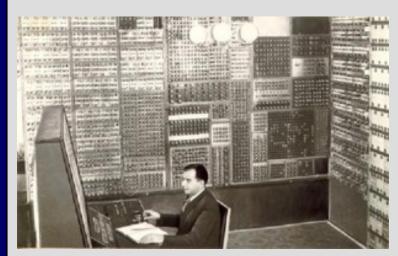


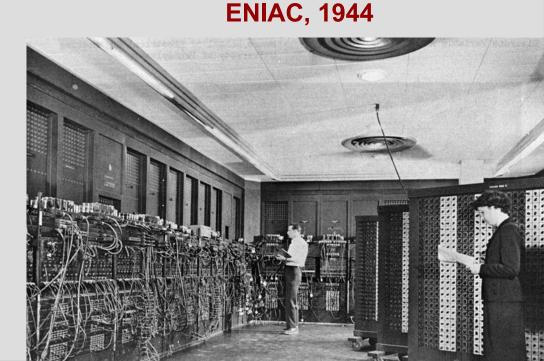
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- Lehmer talk at Symposium on Large-Scale Digital Calculating

M9CM, 1950





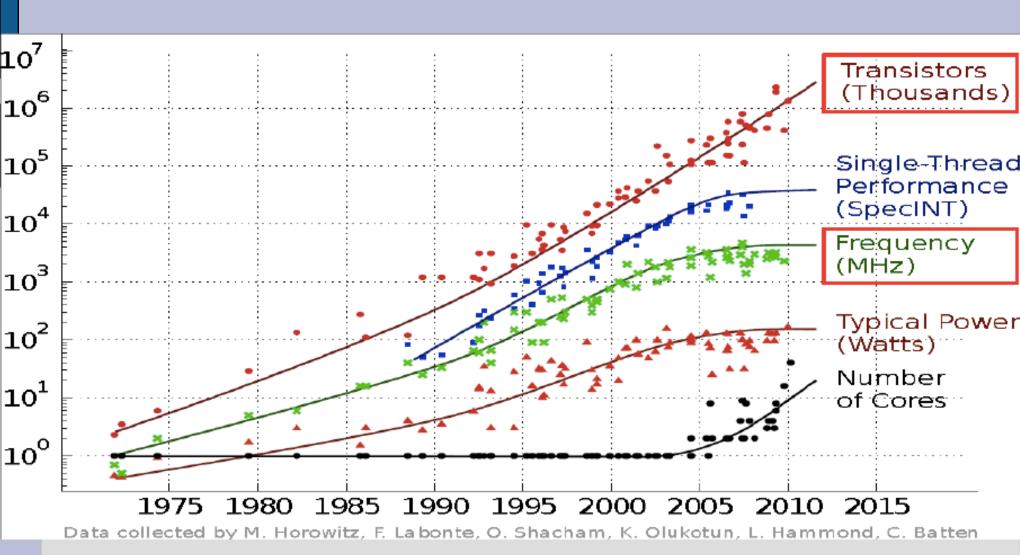
Large scale simulations with parallel annealing algorithm

Outline:

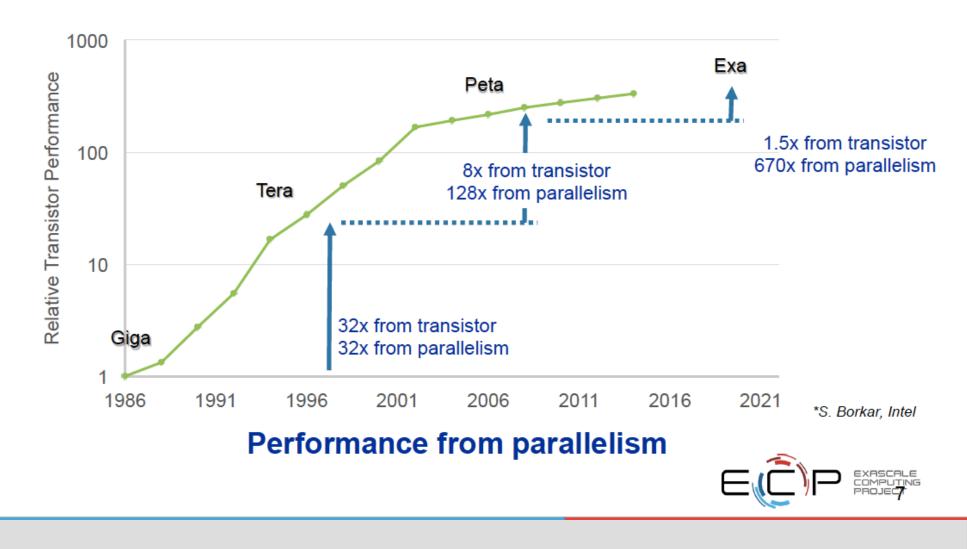
- Motivation
- Population annealing
- Results
- Examples
- Implementation
- Arguments
- Conclusion

Grid-2018, Dubna, 2018-09-11

Moore's law – saturation? Or something new happens?



From Giga to Exa, via Tera & Peta*



From J. Messina, 31 July, 2016 (ECP director, ANL)

Main goal

The big challenge for scientific computing is to develop algorithms and computational frameworks that use the parallel hardware efficiently.

There are two approaches:

- Develop a universal framework which is potentially is fully scalable;
- Invent an algorithm which is efficient for the particular set of problems.

Examples

There are two approaches:

 Develop a universal framework which is potentially is fully scalable;

For example, Parallel Discrete Event Simulation (talk by Lilia Ziganurova on Friday)

• Invent an algorithm which is efficient for the particular set of problems

For example, Population Annealing (this talk).

Population Annealing algorithm

- 1. The population annealing algorithm is designed for study systems with rough free-energy landscapes (spin glasses, optimization problems...).
- Combines the power of the known efficient algorithms simulated annealing, Boltzmann weighted differential reproduction, and sequential Monte Carlo process.
- 3. Bring the population of replicas to the equilibrium even in the low-temperature region.
- 4. Provides a very good estimate of the free energy.
- 5. PopAnn is performed over a large number of replicas with many spin updates, and it is a good candidate for massive parallelism.
- 6. Efficient parallel implementation many replicas.
 - K. Hukushima, Y. Iba, AIP Conf. Proc. 690 200 (2003)
 J. Machta, Phys. Rev. E 82 026704 (2010)

Population Annealing algorithm by Machta (PAM)

- 1. Set up an equilibrium ensemble of $R = R_0$ independent copies (replicas) of the system at inverse temperature β_0 . Often $\beta_0 = 0$, where this can be easily achieved.
- 2. To create an approximately equilibrated sample at $\beta_i > \beta_{i-1}$, resample configurations with their relative Boltzmann weight $\tau_i(E_j) = \exp[-(\beta_i \beta_{i-1})E_j]/Q_i$, where $Q_i = \sum_j \exp[-(\beta_i \beta_{i-1})E_j]/R_{i-1}$.
- 3. Update each replica by θ rounds of an MCMC algorithm at inverse temperature β_i .
- 4. Calculate estimates for observable quantities \mathcal{O} as population averages $\sum_{j} \mathcal{O}_{j}/R_{i}$.
- 5. Goto step 2 unless the target temperature β_{K-1} has been reached.

Population Annealing algorithm by Machta (PAM)

Partition function ratio $Q(\beta_k, \beta_{k-1})$ is given by

$$Q(\beta_k, \beta_{k-1}) = \frac{\sum_{j=1}^{\tilde{R}_{\beta_k}} \exp\left[-(\beta_{k-1} - \beta_k)E_j\right]}{\tilde{R}_{\beta_k}}$$
(1)

and normalized weights $\tau_j(\beta_k, \beta_{k-1})$ calculated accordingly by

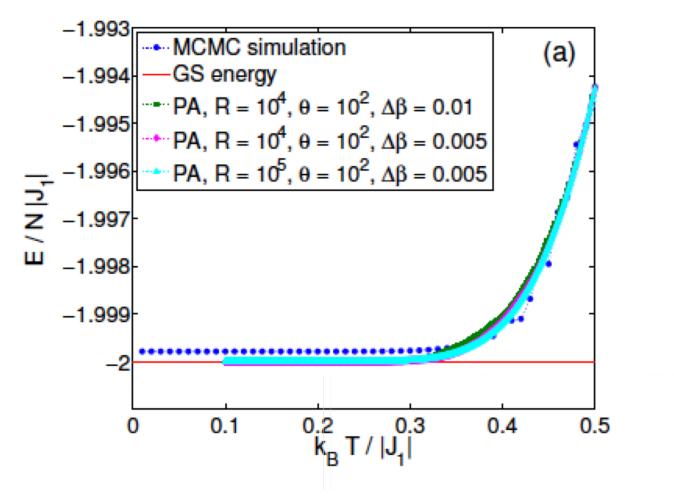
$$\tau_j(\beta_k, \beta_{k-1}) = \frac{\exp\left[-(\beta_{k-1} - \beta_k)E_j\right]}{Q(\beta_k, \beta_{k-1})}$$
(2)

and

$$\tilde{R}_{\beta_k} = \sum_{j=1}^{\tilde{R}_{\beta_k}} \tau_j(\beta_k, \beta_{k-1}). \tag{3}$$

$$-\beta_k \tilde{F}(\beta_k) = \sum_{i=K}^{k+1} \ln Q(\beta_k, \beta_{k-1}) + \ln \Omega$$

PopAnn, CUDA: frustrated Ising ferromagnet on the stacked triangular lattice



EPJ Web of Conferences **108**, 02016 (2016)

Ising model with Population Annealing

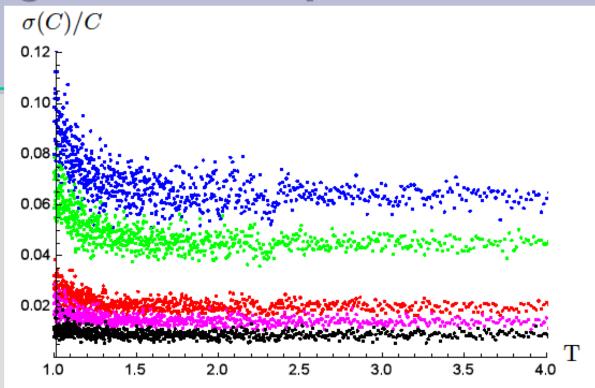


FIG. 5: Relative specific heat errors, $\sigma(C(T))/C(T)$, as a function of the temperature for a different number of replicas $R,\ R=500$ - blue, R=1000 - green, R=5000 - red, R=10000 - pink, and R=25000 - black.

Computer Physics Communications (2017)

Potts model with Population Annealing

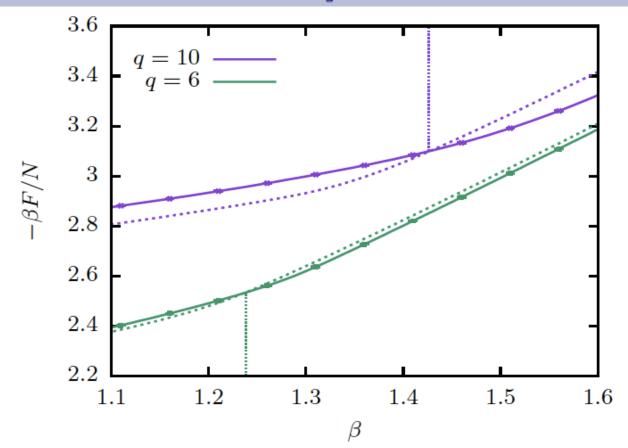
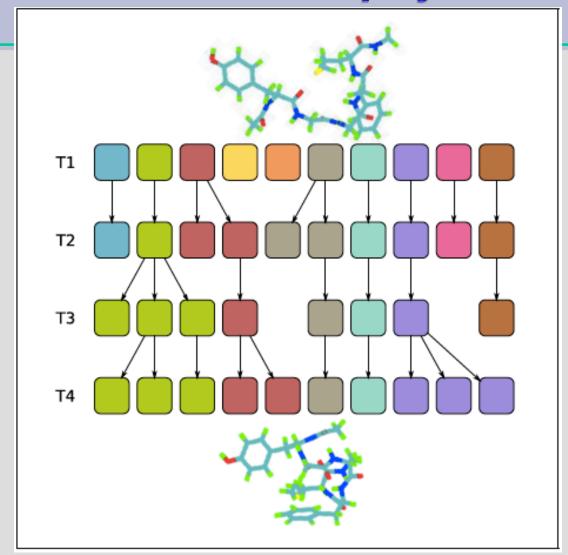


Fig. 2. Metastable free energy for the q-state Potts model with q = 6 (green) and q = 10 (magenta) for a cooling (solid lines) and a heating (dashed lines) cycle. The vertical dotted lines indicate the locations of the transition points β_t . The lattice size is L = 32, and the PA parameters are $\theta = 10$, R = 10000, and $\Delta\beta = 0.01$. Taken from Ref. [27].

Eur. Phys. J. Special Topics **226** 595–604 (2017)

Population Annealing for Molecular Dynamics Simulations of Biopolymers



Population Annealing for Molecular Dynamics Simulations of Biopolymers

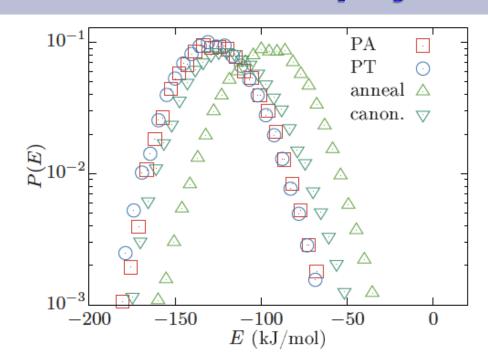


Figure 3: Energy histograms at the lowest temperature, T = 200 K, as obtained from the population annealing (PA), parallel tempering (PT), population annealing without resampling ("anneal"), and canonical ("canon.") simulations, respectively.

GPU accelerated PA algorithm

- (1) initialization of the population of replicas (kernel ReplicaInit)
- (2) equilibrating MCMC process (kernel checkKerALL)
- (3) calculation of energy and magnetization for each replica (kernel energyKer)
- (4) calculation of $Q(\beta, \beta')$ (kernel QKer)
- (5) calculation of the number of copies n_i of each replica i (kernel CalcTauKer)
- (6) calculation of the partial sums $\sum_{i=1}^{j} n_i$, which identify the positions of replicas in the new population (kernel CalcParSum)
- (7) copying of replicas (kernel resampleKer)
- (8) calculation of observables via averaging over the population (kernel CalcAverages)
- (9) calculation of histogram overlap (kernel HistogramOverlap)
- (10) updating the sum of energy histograms $\sum_{i=1}^{K} P_{\beta_i}(E)$ for the multi-histogram reweighting (kernel UpdateShistE)

GPU accelerated PA algorithm

Table 1. Peak performance of the CPU and GPU PA implementations in units of the total run time divided by the total number of spin flips performed, for different system sizes. The best GPU performance is achieved for large θ , and here $\theta = 500$ was chosen for a population of $R = 50\,000$ replicas. GPU performance data are for the Tesla K80 (Kepler card) and GeForce GTX 1080 (Pascal card). The sequential CPU code was benchmarked on a single core of Intel Xeon E5-2683 v4 CPU running at 2.1 GHz.

	time per spin flip (ns)		
	CPU	GPU	GPU
		$({\rm Kepler\ card})$	(Pascal card)
L = 16	23.1	0.094	0.038
L = 32	22.9	0.092	0.034
L = 64	22.6	0.092	0.036
L = 128	22.6	0.097	0.039

Random Number Generation at "large scale"

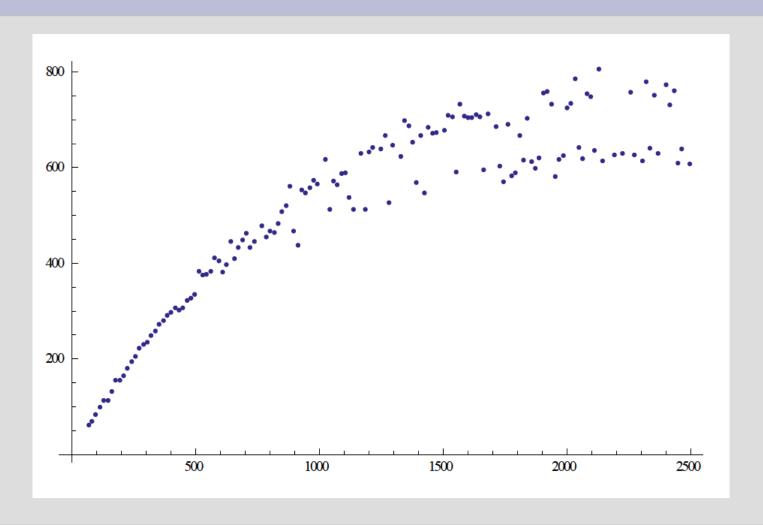
PRAND: GPU accelerated parallel random number generation library: Using most reliable algorithms and applying parallelism of modern GPUs and CPUs (L. Barash, LS, CPC 2014)

Highlights of PRAND - SSE-accelerated, GPU-accelerated, C, Fortran and CUDA, parallel streams

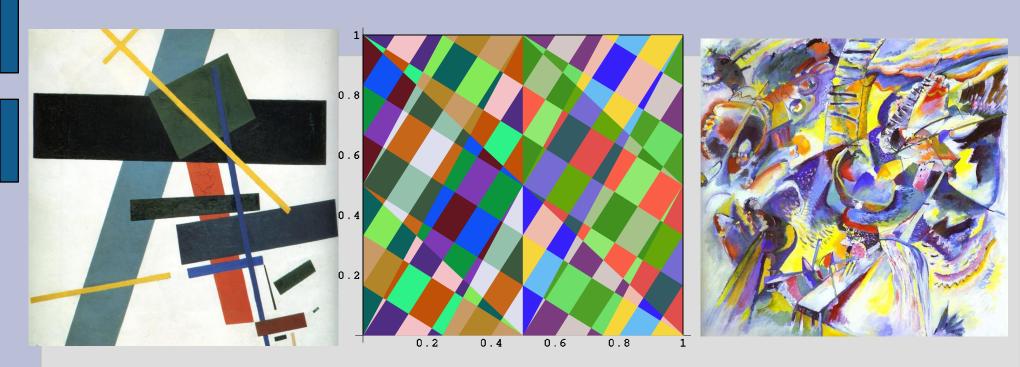
Program summary URL: http://cpc.cs.qub.ac.uk/summaries/AESB_v1_0.html
Program obtainable from: CPC Program Library, Queen's University, Belfast, N. Ireland

MC integral

- MC integral
- Example with 3000 GPGPU (Lomonosov)



PRAND: GM generators (on torus)



Kandisky, Malevich, Barash-Shchur

MPI/GPU PA implementation

Technical problems to solve:

- Load balancing of all GPU nodes with an approximate same number of replicas;
- Minimize large memory exchange between nodes;
- •

Conclusion

- *Population annealing* approach is the promising tool for the number of problems:
- "complex" ground state
- the rough energy landscape
- optimization problems
- *Population annealing* algorithm is the natural candidate for large-scale and *fully scalable simulations* with the *heterogeneous parallelism*.





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International Conference on Computer Simulation in Physics and beyond

September 24-27, 2018, Moscow, Russia

Organized by

National Research University Higher School of Economics Science Center in Chernogolovka Landau Institute for Theoretical Physics

CSP2018 will be held at the building of Moscow Institute for Electronics and Mathematics,
National Research University Higher School of Economics
Tallinskaya ul. 34, Moscow

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